

## The “Clear-Sky Bias” of TOVS Upper-Tropospheric Humidity

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(Manuscript received 10 December 1999, in final form 7 February 2000)

### ABSTRACT

A temporal sampling bias may be introduced due to the inability of a measurement system to produce a valid observation during certain types of situations. In this study the temporal sampling bias in satellite-derived measures of upper-tropospheric humidity (UTH) was examined through the utilization of similar humidity measures derived from radiosonde data. This bias was estimated by imparting the temporal sampling characteristics of the satellite system onto the radiosonde observations. This approach was applied to UTH derived from Television Infrared Observation Satellite (TIROS) Operational Vertical Sounder radiances from the NOAA-10 satellite from the period 1987–91 and from the “Angell” network of 63 radiosonde stations for the same time period. Radiative modeling was used to convert both the satellite and radiosonde data to commensurate measures of UTH.

Examination of the satellite temporal sampling bias focused on the effects of the “clear-sky bias” due to the inability of the satellite system to produce measurements when extensive cloud cover is present. This study indicates that the effects of any such bias are relatively small in the extratropics (about several percent relative humidity) but may be ~5%–10% in the most convectively active regions in the Tropics. Furthermore, there is a systematic movement and evolution of the bias pattern following the seasonal migration of convection, which reflects the fact that the bias increases as cloud cover increases. The bias is less noticeable for shorter timescales (seasonal values) but becomes more obvious as the averaging time increases (climatological values); it may be that small-scale noise partially obscures the bias for shorter time averages. Based on indirect inference it is speculated that the bias may lead to an underestimate of the magnitude of trends in satellite UTH in the Tropics, particularly in the drier regions.

### 1. Introduction

Atmospheric water vapor plays an important role in the maintenance of and natural variations in the climate system and is also postulated to play a crucial part, through a positive feedback, in anthropogenically induced changes in climate resulting from increases in carbon dioxide and other greenhouse gases. Although the absolute amount of water vapor typically decreases by an order of magnitude from the boundary layer to the mid- to upper troposphere, the contribution of each water vapor molecule to the atmospheric greenhouse effect increases by roughly the same amount (Schmetz et al. 1995). Thus, while the amount of water vapor in

the upper troposphere is small, it should be monitored both for understanding the atmospheric circulation as well as studying climate change (Elliott 1995).

Satellite radiances have been used for a variety of purposes in the monitoring of upper-tropospheric humidity (UTH). For example, Bates et al. (1996) found a prominent interannual signal in UTH in the Tropics and subtropics; Geer et al. (1999) examined long-term variability in UTH in the context of climate change; Soden and Bretherton (1994) compared observed and GCM-simulated UTH.

Radiances from the Television Infrared Observational Satellite (TIROS) Operational Vertical Sounder (TOVS), an infrared sensor that has been operated on the National Oceanic and Atmospheric Administration (NOAA) series of satellites since late 1978, are a popular means by which to study UTH. Recently, Soden and Lanzante (1996, hereafter referred to as SL) have made use of the TOVS data to make inferences regarding spatial inhomogeneities in radiosonde measures of UTH caused by country-specific instrumental biases. One major finding of SL was that the satellite observations sug-

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gest a systematic difference (bias) of about 15%–20% (in terms of relative humidity) between two different types of radiosonde hygrometers. Another issue that was examined by SL, albeit superficially, concerns the satellite “clear-sky bias” (CSB) that results from a temporal sampling bias. They utilized radiosonde observations to make inferences regarding the satellite CSB and concluded that this effect introduces a modest dry bias in the satellite climatology. This work extends the analyses of SL and examines in more detail the satellite CSB (in TOVS UTH). It is worth noting that because SL used all available radiosonde stations their results were skewed toward the extratropical landmasses of the Northern Hemisphere; here a more limited but more uniformly distributed network of stations is used. The purpose of this paper is to demonstrate that a statistically significant CSB exists, to document some of its spatial and seasonal variability, and to give rough estimates of its magnitude. Given the limited data sample used, discussion concentrates on the gross features of the bias.

One potentially serious complication in the analysis of both radiosonde and satellite measurements of water vapor is the presence of temporal inhomogeneities. Discontinuities may be introduced into the radiosonde record through country- and station-specific changes in instrumentation and recording practices, which are sometimes not documented. With regard to satellite records, temporal inhomogeneities can be introduced through changes in satellites and by orbital drifts that may occur over the lifetime of an individual satellite. In order to minimize problems with continuity we have chosen to analyze data from a single satellite (*NOAA-10*) having nearly a 5-yr period of record. Furthermore, *NOAA-10* has only a small orbital drift over its lifetime (see Fig. 1 of Bates et al. 1996). With regard to the radiosonde data, cursory examination of Gaffen (1992, 1996) suggests that at least two-thirds of the stations used herein probably have no major discontinuities over this time period. Given the intent to draw conclusions only on the gross nature of the CSB, any such remaining effects should not be a hindrance.

Section 2 presents the framework used for estimating the CSB, while section 3 consists of a discussion of the two datasets employed in this study along with some related aspects of the statistical methodology. The exploration of the CSB in the context of the satellite temporal sampling bias is presented in section 4, while section 5 presents a brief summary.

## 2. Framework for evaluation of bias

The estimation of the temporal sampling bias in the satellite measurements is achieved by imparting the satellite temporal sampling characteristics onto the radiosonde data; the radiosonde observations are used to infer what has happened when the satellite observations were missing. In practice this is carried out by partitioning the radiosonde sample conditional on whether a satellite

observation was present or missing. Using such a framework there are two reasonable ways to define the satellite temporal sampling bias:

$$\text{TSB} = \text{med}(R_N) - \text{med}(R_S) \quad \text{and} \quad (1)$$

$$\text{TSB}^* = \text{med}(R) - \text{med}(R_S). \quad (2)$$

Here  $R$  represents relative humidity values from different sets of radiosonde observations and  $\text{med}$  indicates the median operator. The totality of radiosonde observations ( $R$ ) consists of radiosonde observations for which no contemporaneous satellite observation is present ( $R_N$ ) and radiosonde observations for which the satellite observation is present ( $R_S$ ). It should be noted that the median rather than the arithmetic mean is used throughout this study because of the non-Gaussian nature of UTH. A non-Gaussian distribution is expected, and indeed observed, because of skewness and the boundedness of relative humidity between 0% and 100%. Furthermore, all of the statistical tests and measures used here (as described by Lanzante 1996) are nonparametric in order to provide tolerance to this non-Gaussian behavior.

There is an expectation that the temporal sampling bias should be positive because the cases that the satellite misses should have systematically higher humidity due to the presence of clouds that inhibit satellite measurements (as discussed in section 3a). It should be noted that observations may be missing for reasons other than those that would produce the expected bias. For example, a satellite may not always scan a particular region each day, or a processing or transmission error may render the observation unusable. However, there still can be a *systematic* error if these other reasons for failure are random (i.e., are not related to the level of the humidity) or if they occur so infrequently so as to have little impact.

The examination of CSB by SL was done in a limited manner and employed a measure analogous to (2), except that SL employed the arithmetic mean as opposed to the median. Ideally the two different ways of defining the bias, TSB versus TSB\*, represent the difference in the medians for “cloudy” minus “clear” versus “total” minus “clear,” respectively. The advantage of using TSB\* is that it is an appropriate quantitative *estimate* of the bias expected in practice since the total distribution represents “reality” in the absence of any temporal sampling bias while clear represents the sample that one has available in practice given the temporal sampling bias. On the other hand, TSB is a more appropriate measure for *detecting* the presence of a clear-sky bias using testing methods based on probability and statistics; in this case the procedure is to determine whether or not the separate (exclusive) samples of clear and cloudy cases are statistically different (e.g., if they have different medians).

When the two measures of clear-sky bias, given by (1) and (2), are redefined using the arithmetic mean

instead of the median, then a simple relationship between the two can be derived algebraically. Although not strictly applicable since this study employs the median, this relationship can serve as general guidance and is given by

$$\overline{\text{TSB}}^* = \overline{\text{TSB}} / (1 + M_S/M_N), \quad (3)$$

where  $M_S$  and  $M_N$  are the number of observations in the clear and cloudy samples, respectively, and the overbar is used to denote that means have been used instead of medians. If the two samples have equal numbers of observations then the ratio of  $\overline{\text{TSB}}^*$  to  $\overline{\text{TSB}}$  is  $1/2$ . In this study the cloudy cases (i.e., missing satellite observations) generally account for 40%–60% of the total sample, which implies that the ratio of  $\overline{\text{TSB}}^*$  to  $\overline{\text{TSB}}$  generally ranges from 0.4 (in clearer regions) to 0.6 (in cloudier regions). Since assessment of statistical significance is a major goal of this work TSB is primarily employed in the presentation of results although most of the analyses have been repeated using  $\overline{\text{TSB}}^*$ . Later in this paper  $\overline{\text{TSB}}^*$  is used in the quantitative estimate of clear-sky bias.

### 3. Data and statistical methodology

#### a. Satellite data

The satellite data used in this study consist of a subset (both temporally and spatially) of the data used by SL and described in more detail therein. Here we use data from only one of the NOAA polar orbiting satellites (*NOAA-10*), which covers the time period January 1987–September 1991. Additionally, satellite data are used only at locations corresponding to the network of radiosonde stations (described below); the original data were available on a  $2.5^\circ \times 2.5^\circ$  grid representing area averages.

The basic data are the TOVS  $6.7\text{-}\mu\text{m}$  water vapor brightness temperature measurements. This quantity is primarily sensitive to relative humidity in the upper troposphere (Soden and Bretherton 1993). However, it actually represents a weighted average of relative humidity throughout a layer, rather than humidity at or near a single level. It should be noted that the vertical weighting (sensitivity) function varies such that it is slightly lower (higher) for cold/dry (warm/moist) profiles. Weighting functions for typical tropical and winter mid-latitude soundings are given in Fig. 1a of SL and are centered near 375 and 500 hPa, respectively; there is significant weighting in regions roughly 125–150 hPa above and 250 hPa below the center. The reader is cautioned that in polar regions (having only a few of the stations in our network) the weighting function drops to the mid- and lower troposphere, so the term UTH is a bit of a misnomer. In SL the random strong line model of Soden and Bretherton (1996) was used to generate an index of UTH (expressed as a relative humidity) from the brightness temperature. This UTH index corre-

sponds to average relative humidity with the previously mentioned vertical weightings and is used in the analyses herein instead of brightness temperature.

Because clouds greatly attenuate infrared radiation, it is necessary to apply a “cloud-clearing” technique that is based on the method introduced by McMillin and Dean (1982) in order to correct the brightness temperature measurements for the presence of clouds; for details and references the reader is referred to SL. However, if cloud cover is too extensive ( $>75\%$ ) this technique cannot be used and the observation is treated as missing, potentially leading to a clear-sky bias.

#### b. Radiosonde data and simulations

The radiosonde data used here are part of an updated version of the archive maintained at the Geophysical Fluid Dynamics Laboratory as described by Oort and Liu (1993). Used here are all available soundings for the “Angell network” of 63 stations (Angell and Korshover 1977) which is discussed and depicted in Oort and Liu (1993); in contrast, SL used the full global network of ( $\sim 800$ ) stations. These 63 stations were chosen by Angell on the basis of continuity/quality of record and in order to give reasonable global coverage. The period of record used here is by necessity identical to that for the satellite data (January 1987–September 1991). The radiosonde record is fairly complete. For example, about two-thirds of the stations have humidity observations reported at the 500-hPa level at least 85% of the time, about one-fifth have around 50% or more of the possible observations, and only the remaining few stations have too few observations for meaningful analyses.

The radiosonde data have been transformed as discussed in greater detail by SL using the operational TOVS transmittance model that is described by Weinreb et al. (1981). Each observed radiosonde profile of humidity and temperature has been inserted into this model in order to simulate the brightness temperature that would be observed under these conditions. This simulated brightness temperature is then converted to a UTH index in the same manner as for the observed satellite brightness temperature. The use of this simulation procedure renders radiosonde water vapor measurements in terms of a quantity commensurate with that from the satellite.

In addition to the use of the UTH index, analyses have also been repeated using the observed radiosonde 500-hPa relative humidity; results are generally quite consistent qualitatively. The choice of the 500-hPa level was motivated by the fact that this is generally regarded to be the highest level for which radiosonde water vapor measurements are reasonably reliable outside of the Tropics (Elliott 1995) and that the satellite sensitivity function should be reasonably large at this level for most profiles. Raw (500 hPa) radiosonde relative humidity has been used as a consistency check since the simu-

lation procedure does involve certain assumptions (see SL for details) and since it is not always possible to perform the simulation even when the 500-hPa humidity is reported; if the temperature or humidity coverage is insufficient in the remainder of the profile (usually the upper portion is the problem), the simulated value is recorded as missing.

### c. Other data considerations

For both satellite and radiosonde data daily averages were used and analyses were performed separately for each of the four standard 3-month season types (DJF, MAM, JJA, and SON). A minimum of 90 observations (roughly one-quarter of the possible observations) are required for the climatological (seasonal) analyses performed here, whereas for analyses in which a seasonal value or anomaly is computed for a given season of a given year the minimum number of observations required *per season* was 23 (which is about one-quarter of  $\sim 90$  days per season). For temporal sampling bias calculations, in which the sample is partitioned, the required minimum is applied separately to each of the two partitions. For the majority of stations 500-hPa relative humidity (simulated UTH) is observed at least 90% (80%) of the time. By contrast, satellite UTH is available only 40%–60% of the time. The relatively large amount of missing satellite data is a manifestation of the temporal sampling bias, and the fact that the radiosonde data have relatively little missing data facilitates their use in studying this bias.

### d. Statistical methodology

The non-Gaussian distribution of UTH, as well as its temporal and spatial coherence complicate the statistical analyses of this study. Because of the non-Gaussian behavior, a number of nonparametric techniques have been used as alternatives to their more traditional counterparts (given in parentheses): median (arithmetic mean), Spearman rank-order correlation (Pearson product moment correlation), median of pairwise slopes regression (least squares regression), and the robust rank-order test (two sample Student's *t*-test). The rationale and theoretical basis, examples, and technical details of the above alternatives can be found in Lanzante (1996).

In the assessment of statistical significance a complication arises that is common in studies involving meteorological data, namely, the data may be correlated both in time (successive observations are not independent) and space (different stations are not independent). With regard to spatial interdependence the concept of field significance as addressed by Livezey and Chen (1983) is relevant: if a certain number of individual stations are deemed significant how likely is it that the whole collection (i.e., the entire map) is significant, given that there is some degree of correlation among the stations?

The approach used here to deal with these interdependencies is to reduce the degrees of freedom in assessing significance; one may assume that every *n*th observation in time, and/or every *m*th station in space are “effectively independent.” For example, for the midlatitudes it might be reasonable to assume that humidity is independent every third day, given the typical frequency of cyclonic systems and changes of air masses. In fact this is a conservative estimate of significance because the original time series is already less coherent due to gaps resulting from missing data; recall that about 40%–60% of the days have no satellite observation. To be more stringent, estimates can also be made assuming every 6th (probably too severe) or 9th (almost certainly too severe) observation is effectively independent. This approach, although not statistically rigorous, is commonly used by meteorologists. Here, a comparison is made between the results using more than one reduction in degrees of freedom (ranging from the more liberal to the more conservative) in order to cover the uncertainty in the assumed reduction.

## 4. Satellite temporal sampling bias

The issue of clear-sky bias was touched upon by SL using data from a single season (JJA 1989) and by aggregating results over all stations. This issue is examined here in more detail by using a larger temporal sample (almost 5 yr) and considering its spatial and seasonal structure. It should be noted that much of the discussion here is based on TSB rather than TSB\*, although both have been examined, because the former is preferred for hypothesis testing. Also, the bias maps are expressed in terms of 500-hPa relative humidity rather than simulated UTH [i.e., by applying Eq. (1) to 500 hPa instead of UTH] because the former results in more stations with sufficient data for analysis. Later in this section assessments are made in terms of TSB\* derived from simulated UTH. Since there is qualitative agreement between the related measures, and in the interest of brevity, only selected measures are presented.

Maps of TSB expressed in terms of 500-hPa relative humidity for DJF and JJA are shown in Figs. 1 and 2, respectively. In these figures filled squares denote statistical significance at the 5% level while open circles indicate lack of such significance. In examining these figures along with the corresponding ones for MAM and SON (not shown) the most striking aspect is the band of significant and larger-magnitude TSB that can be seen migrating seasonally through the Tropics, apparently in association with areas of convection. During DJF, the significant stations in the Tropics are located mostly near or south of the equator. With the northward seasonal migration, by JJA the areas of significance are located mostly north of the equator. Also noteworthy is the fact that by JJA almost all of the midlatitude stations in the Northern Hemisphere have become significant, evidently associated with the seasonal enhancement of con-

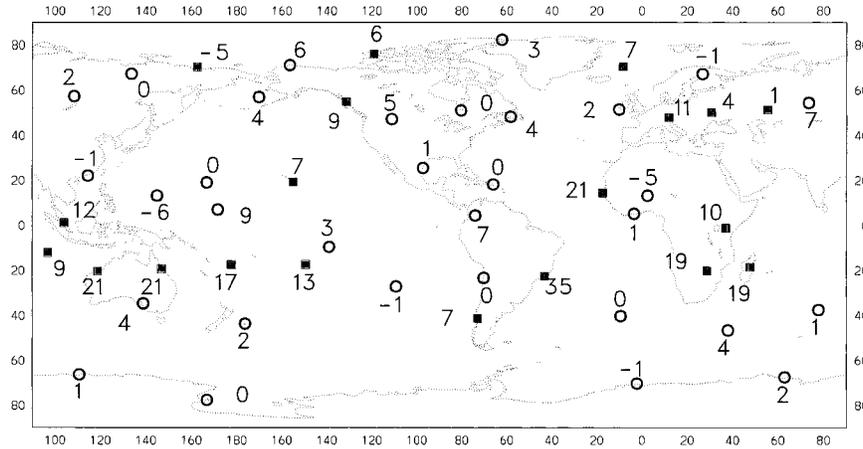


FIG. 1. The DJF temporal sampling bias (TSB) estimated by applying 500-hPa relative humidity (in percent) to Eq. (1). Significance (nonsignificance) at the 5% level is indicated by filled squares (open circles). Significance was determined by applying the robust rank-order test (Lanzante 1996), assuming the degrees of freedom are equal to one-sixth the actual sample size in order to account for the temporal coherence in the daily data; there is little sensitivity of the results to this assumption. This test determines if the median of the two samples,  $R_N$  and  $R_S$  from Eq. (1), are significantly different. This map (as well as corresponding maps for MAM, JJA, and SON) is highly field significant (Livezey and Chen 1983) since map significance at the 5% level is obtained even assuming every 10th station is independent.

vection. Related to this is the fact that over the mid-latitudes of North America and eastern Asia there is a distinct seasonal cycle with larger and more significant TSB during the warm/convective seasons (JJA/SON).

Closer examination of the seasonal maps of TSB, in conjunction with corresponding climatological maps (not shown), suggests that in the Tropics the seasonal migration of the bias (associated with areas of convection) is also related to the level of humidity; in other words, there is a larger bias where the humidity is higher.

In order to explore this relationship, correlation analyses have been performed separately for each season by aggregating values from the different station locations; however, in order to simplify the presentation, the four seasonal correlations have been averaged and are given in Table 1. The seasonal correlations were computed using TSB and UTH expressed in three different forms:

1) climatology, 2) total, and 3) anomaly. For form 1, each value that enters into the correlation is a climatological median (of all daily values for the given season from 1987 to 1991). For form 2, the actual seasonal values (computed as the median of all available days in the given season), one seasonal value per year, are used. For form 3, the values are similar to those of 2 except that they are expressed as seasonal anomalies. These three forms represent different averaging timescales from longest (form 1) to shortest (form 3). In this table UTH is correlated with TSB both using all available stations and using only those in the Tropics.

The correlations in Table 1 suggest that in the Tropics TSB increases as UTH increases and that the strength of this relationship increases as the averaging timescale increases (i.e., from anomaly to total to climatology). The timescale dependence may reflect the fact that the

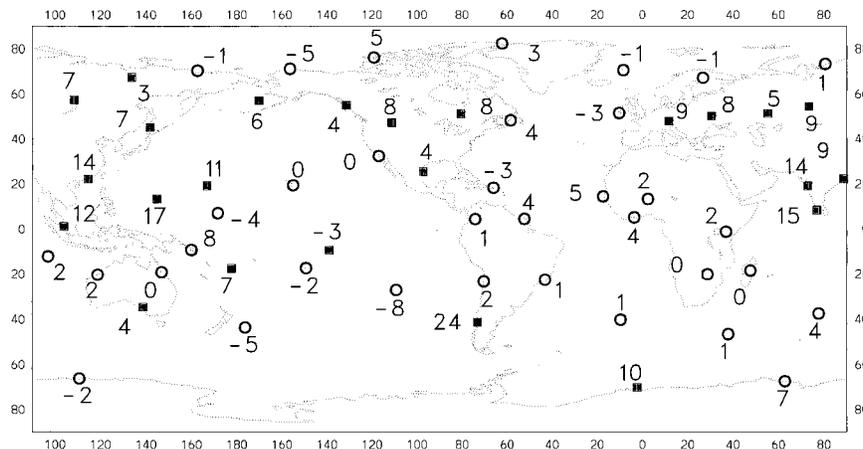


FIG. 2. Same as Fig. 1 except for JJA.

TABLE 1. Average Spearman correlation coefficient (average of four seasonal values) between satellite UTH and TSB. Correlations use either all available stations (All) or just those from 30°N–30°S (Tropics). “Climatology” uses the climatological median at each station while “Total” (“Anomaly”) uses the seasonal median (anomaly of the season median) at each station for each season in the sample. Significance at the 5% level is indicated by one, two, or three asterisks assuming degrees of freedom equal the sample size times 1/3, 1/6, or 1/9 (1/6, 1/9, or 1/12) for climatology total, and anomaly, respectively; these reductions in degrees of freedom are meant to account for the spatial coherence (spatial and temporal coherence) for correlations based on climatology (total and anomaly). The averages have been computed by using Fisher’s  $z$  transformation (Zar 1974), as was done by Soden and Lanzante (1996), and weighting by the sample size.

	All	Tropics
Climatology	0.16	0.66**
Total	0.10	0.39***
Anomaly	0.10	0.13

effects of random noise are diminished as the “averaging time” increases. It is worth noting that the satellite measure has actually been derived using data over an *area* whereas the radiosonde UTH represents nearly a *point* measurement. Given this mismatch one would expect that smaller-scale variations could degrade the relationship between the two; however, as more cases are included (i.e., longer averaging time) the “true” relationship would become more apparent, as the radiosonde *point* becomes more representative of the satellite *area*.

The results presented thus far seem to suggest that in the more convectively active regions not only is the bias larger and more significant, but in addition the relationship between the bias and UTH is stronger as well. As to why this is the case we speculate that the preference toward convection may be due to the deeper *vertical coherence* of moisture and clouds. While the presence of extensive clouds (at any vertical level) may result in a missing satellite observation, in the extratropics clouds may occur at mid- or lower levels when the upper levels are relatively dry, which would cancel, at least partially, the expected relationship. However, vertical transport associated with convection would tend to ensure that when extensive clouds are present the UTH is relatively high. Furthermore, the simplest interpretation of the correlation results is that a time interval with higher median UTH in the Tropics would generally have more days of convection (which contribute to making TSB more positive).

While Table 1 indicates that for tropical stations there is some tendency for TSB to be larger where the UTH is larger, further examination suggests that this relationship is not strictly linear. Figure 3 shows a plot of climatological medians of UTH versus TSB using only tropical stations and combining values from all four seasons. Points with UTH less (greater) than the median (of all values in the figure) are open (filled) circles and the regression line is based on all points. It appears that for the drier stations there is a better linear relationship;

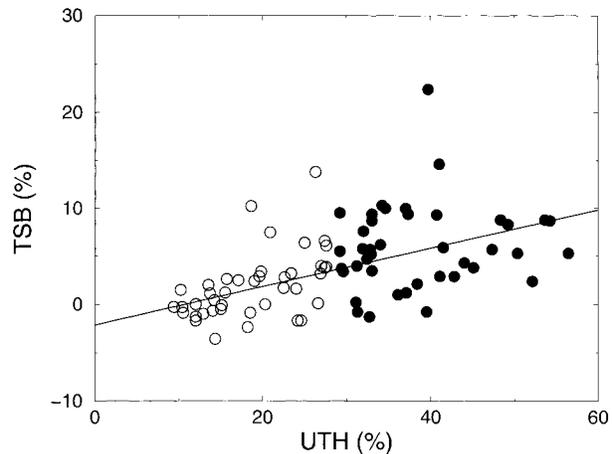


FIG. 3. Climatological medians of simulated UTH when satellite UTH is present (abscissa) and TSB (ordinate) for each tropical station (30°N–30°S) having at least 90 observations of simulated data when the satellite UTH is missing and when it is present; values are from all four seasons. Open circles denote values less than the median (of all values in the figure) while filled circles are for values greater than the median. The line is based on (median of pairwise slopes; Lanzante 1996) regression analysis applied to all of the values (open and filled circles).

the wetter stations show much more scatter. This non-linearity is quantified in Table 2, which presents regression and correlation coefficients based on all values and separately for those below and above the median. It can be seen that most or all of the relationship comes from the drier stations. Perhaps this is simply a reflection of the fact that moister stations have a greater frequency of convection, which is associated with smaller spatial and temporal scales leading to higher sampling variability.

While globally the TSB is overwhelmingly positive there are some instances in which it is near zero or negative. There is some tendency for these to occur in subtropical and polar regions. At such stations it is implied that there are cases in which lower UTH is observed when a satellite observation is missing. These cases could occur when low clouds occur preferentially when UTH is lower. In some subtropical regions there is strong downward motion associated with dry conditions aloft that cap a shallow, moister boundary layer. Stronger capping of the inversion (which enhances low clouds) are associated with stronger subsidence and drier conditions aloft. Breakdowns of the inversion result

TABLE 2. Regression slope (median of pairwise slopes),  $b$ , and Spearman correlation coefficient,  $r$ , using all of the values (open and filled circles), “dry” values (open circles), and “wet” values (filled circles) shown in Fig. 3. See caption for Fig. 3 for more details.

	$b$	$r$
All values	0.20	0.59
Dry values	0.28	0.60
Wet values	0.09	0.15

in upward transport of moisture, which dries the boundary layer (reducing cloudiness) but moistens upper levels. In polar regions the strongest low-level inversions (associated with low clouds and fog) occur under the most anticyclonic conditions, which are associated with dry air aloft; a similar mechanism may be in effect in midlatitude coastal locations characterized by frequent fog.

As discussed earlier, estimating clear-sky bias using TSB based on 500-hPa relative humidity (Figs. 1, 2) proves useful for discussion of the patterns and significance. However, TSB\* computed from simulated UTH is the more appropriate quantitative measure of bias in observed satellite UTH. Based on results not shown, use of 500-hPa humidity instead of simulated UTH results in a magnification of the magnitude of the bias estimate by a factor of  $\sim 2$  while [in accordance with Eq. (3)] the use of TSB instead of TSB\* results in a magnification of  $\sim 2.0$ – $2.5$ . In an overall sense, based on the combination of these two factors the effective clear-sky bias on satellite UTH is  $\sim 20\%$ – $25\%$  of the values shown in Figs. 1 and 2, although at individual stations this may vary. Given the inherent noise noted earlier, Figs. 1 and 2 (in light of this reduction) should be interpreted broadly without emphasis on smaller details. In this spirit it can be summarized that the overall clear-sky bias is a few percent, perhaps slightly less than the 4% estimate made by SL, whose Fig. 14 was biased toward the Northern Hemisphere landmasses during JJA; during the warm/convective seasons, especially over continental areas, the estimate made by SL seems appropriate. However, in the most active convective regions (which were disproportionately undersampled by SL) the bias is typically  $\sim 5\%$ – $10\%$ . The geographic dependence and seasonality of the bias is an important aspect that was not explored by SL.

The seasonal and geographical dependence of the satellite CSB has implications for climate monitoring and assessment. However, given the noise noted earlier it seems as if this bias may have limited impact on very short-term climate monitoring; based on examination of maps of CSB for individual seasons (not shown) in this admittedly modest sample it is often difficult to notice the expected bias because of the noise. However, as longer timescales are considered, such as for multiyear events or trends, and in estimating a long-term climatology the geographical and seasonal variations become important in the areas noted earlier.

The dependence of TSB on UTH in the Tropics (as revealed in Table 1) also raises some concern of the effects of a CSB on long-term trends. Unfortunately the given sample is too short to directly address this issue. Furthermore, because of continuity issues it may not be so straightforward to combine the measurements from the different NOAA satellites. If it is assumed that the spatial variability in the bias can be used to infer the temporal variability in the bias, then Table 1 implies that satellite UTH in the Tropics will underestimate the

magnitude of trends (both positive and negative). A simple explanation is that as UTH increases (decreases) with time this implies more (fewer) cloudy days and more (fewer) missing “moist” satellite observations, which results in a larger (smaller) underestimate of UTH with time. An estimate of the magnitude of the effect can be obtained from the regression slopes of Table 2; since these values are based on TSB the appropriate slope (based on TSB\*) is about half [as implied by Eq. (3) and other analyses, not shown], which is  $\sim 0.15$ . So, for example, a satellite trend of 1% relative humidity over some interval might imply a true trend of 1.15%.

## 5. Summary and discussion

In this study, based on an extension of an approach introduced by Soden and Lanzante (1996), radiosonde observations have been used to assess a potential satellite temporal sampling bias. The methodology has been applied to upper-tropospheric humidity (UTH) derived from satellite (TOVS) and radiosonde data taken at the global network of 63 “Angell stations.” Consistent with SL a modest (relative humidity of a few percent) “clear sky bias” was found in the satellite observations, indicating that the satellite systematically misses the moistest cases because they are also the cases with most extensive cloud cover (which may prevent successful observation). However, in more limited regions in the Tropics (where convection is most extensive) a larger bias ( $\sim 5\%$ – $10\%$  relative humidity) may occur. The seasonal evolution of the bias also reflects the seasonal migration of convection. In the Tropics this bias increases as UTH increases. While this bias is clearly seen for longer time averages, such as the climatology over a several-year period, on shorter timescales (individual seasons) the signature of the bias was not clearly evident.

Additionally, it is speculated that in the most highly convective regions the satellite may underestimate (by a fraction of  $\sim 0.15$ ) the magnitude of trends of UTH. With regard to this last point it is worth noting (as pointed out by Geer et al. 1999) that the water vapor feedback hypothesized in the context of “global warming” presents a complication in the use of UTH trends for climate change detection. This is so because as warming occurs, and specific humidity increases, relative humidity may be approximately constant. Nevertheless, dynamical feedbacks could still lead to trends in UTH.

It is important to keep in mind the limitations of this study with regards to the spatial and temporal sampling used. These limitations may explain some of the curious findings: 1) the spatial noise in the maps of the clear-sky bias, 2) the fact that the strength of the linear relationship (positive) between bias and UTH in the Tropics increases as the averaging time increases, and 3) the fact that this linear relationship in the Tropics is stronger in the drier regions. There are several factors that could explain these findings in terms of statistical noise. First,

because convection plays a role, the associated time- and space scales are smaller and thus noisier. Next, there is an inherent mismatch between the satellite UTH, which is representative of an area, and the radiosonde UTH, which is a point estimate. Finally, higher UTH seems to be associated with more frequent convection, which should lead to more noise. It is possible that these sources of noise are entirely responsible for findings 2 and 3 above, in which case the bias is more pervasive than the findings here would suggest, possibly to the extent of having a noticeable effect on short timescales and in all regions of the Tropics. While this study cannot address these issues, the use of a larger sample (a longer time period) may provide guidance, although other complications may arise in such an endeavor related to the continuity of the satellite and radiosonde sensing systems.

One of the motivations for this work was the fact that the relatively long period of record of infrared satellite measurements (since 1978) makes them a very valuable resource for studying UTH. Recent work (Berg et al. 1999) suggests that similar measures of UTH derived from microwave sensors suffer from less of the type of bias examined herein. While at present less than a decade of suitable microwave data is available, microwave sensors hold promise for the future.

*Acknowledgments.* Brian Soden kindly provided the satellite data as well as the code that implements the transmittance model (OTTM). Useful comments and suggestions were provided by Brian Soden and Bram Oort throughout the course of this project, and by Brian Soden and Gabriel Lau in the review of this manuscript. The anonymous reviewers have also provided a number of worthwhile suggestions. We also acknowledge the enthusiastic support and encouragement of Jerry Mahlman towards issues of data quality assessment. Support for one of us (GEG) was provided through the Summer Research Program administered by the Atmospheric and Oceanic Sciences Programs (AOSP) of Princeton University.

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